A Machine-Learning Tool for Visual Risk Analysis and Manager Selection.

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1 November 2023

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Helvetia Insurance.

3rd largest insurer in Switzerland by premium volume 2022

- Also active in France, Italy, Germany, Austria, Spain, United States, Singapore, and the UK
- Approximately 7 mln. customers
- Premium income approximately CHF 11 bn. in 2022
- Approximately 12,500 employees

Asset Management: CHF 47 bn (H1, 2023) or USD 51 bn AuM

Apart from its balance sheet, HV manages a family of mutual funds, Approximately CHF 420 mln

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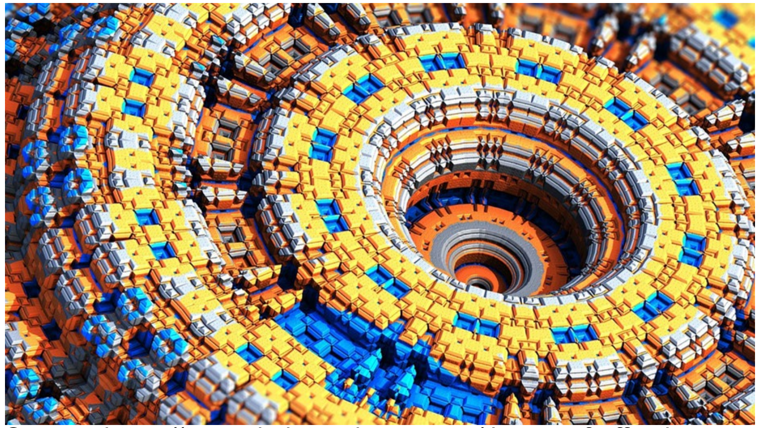
Visual Risk Analysis.

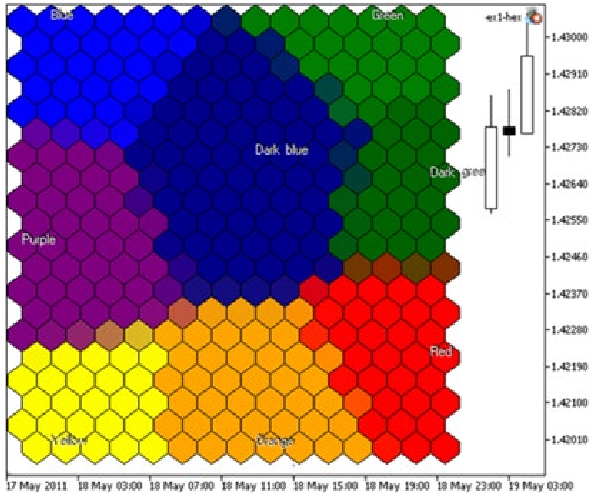
- Use ML tools to better understand structure in data
- Self-Organising Map ↔ visualisation
  - For example, manager selection or risk analysis (e.g., Huber (2019a, b))
- Two use cases:

1) We were offered a Long Vol Strategy as addition to equities / bond fund
   - Does it provide "bang for the buck"?
   - How does it compare to competitors?
2) Can we use characteristics of the visualisation for portfolio construction?

- Provide a fresh perspective to "classic" research
  - Can help to understand problem and suggested solutions better
  - Could we gain new insights from such tools?
  - Decision support
  - Expectation management: not a money machine



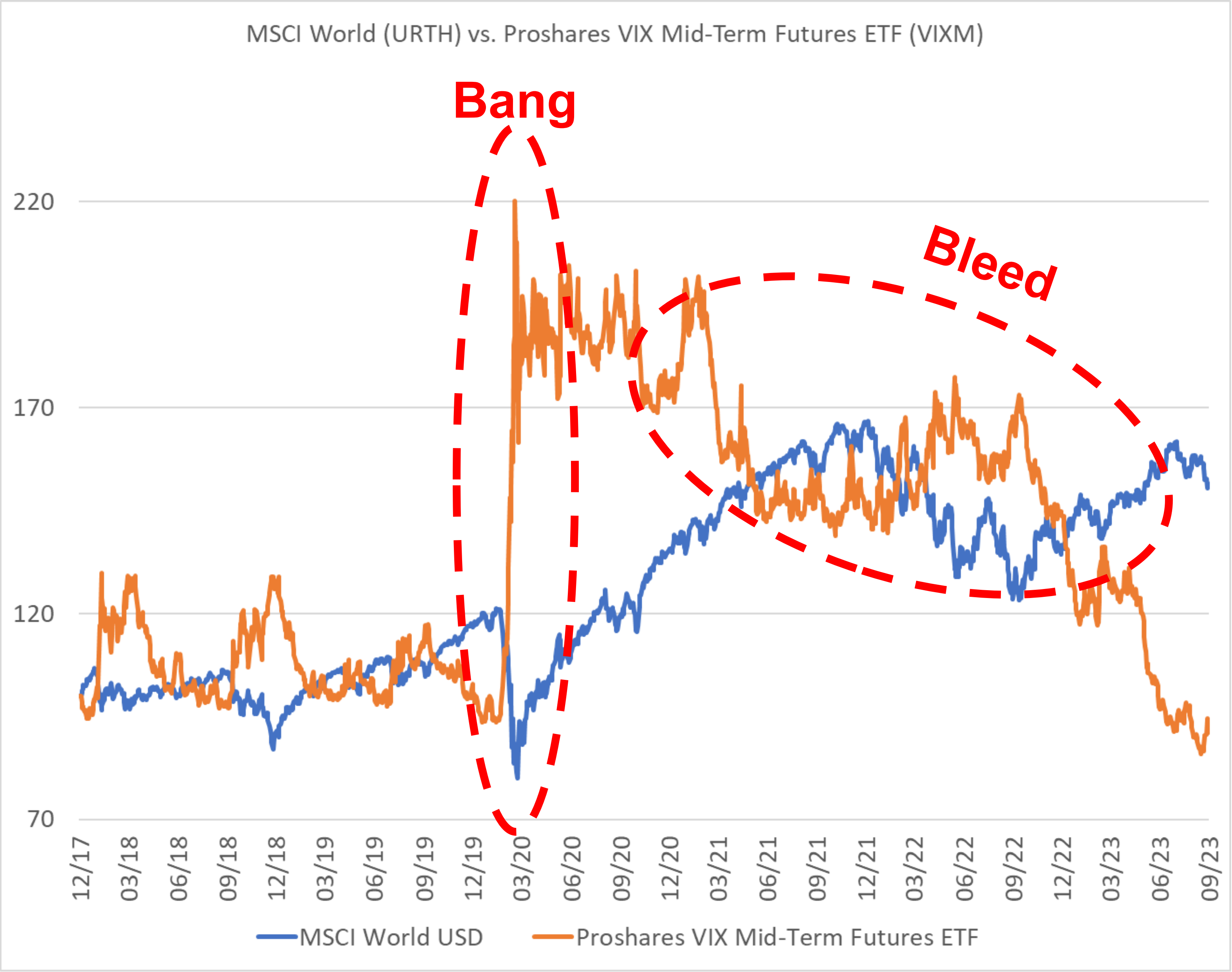
Source: https://towardsdatascience.com/the-art-of-effective-visualization-of-multi-dimensional-data-6c7202990c57



Source: https://www.mql5.com/en/articles/283

1) Long Volatility.

- Long Vol Strategy ↔ market stress
- Long Vol Strategies typically help in stress scenarios, but lose money in "normal" times
- Desired outcome would be:
  - Deliver levered positive performance in times of stress
  - Keep "bleed" as low as possible
- Long Vol Strategies potentially interesting as an addition to a portfolio



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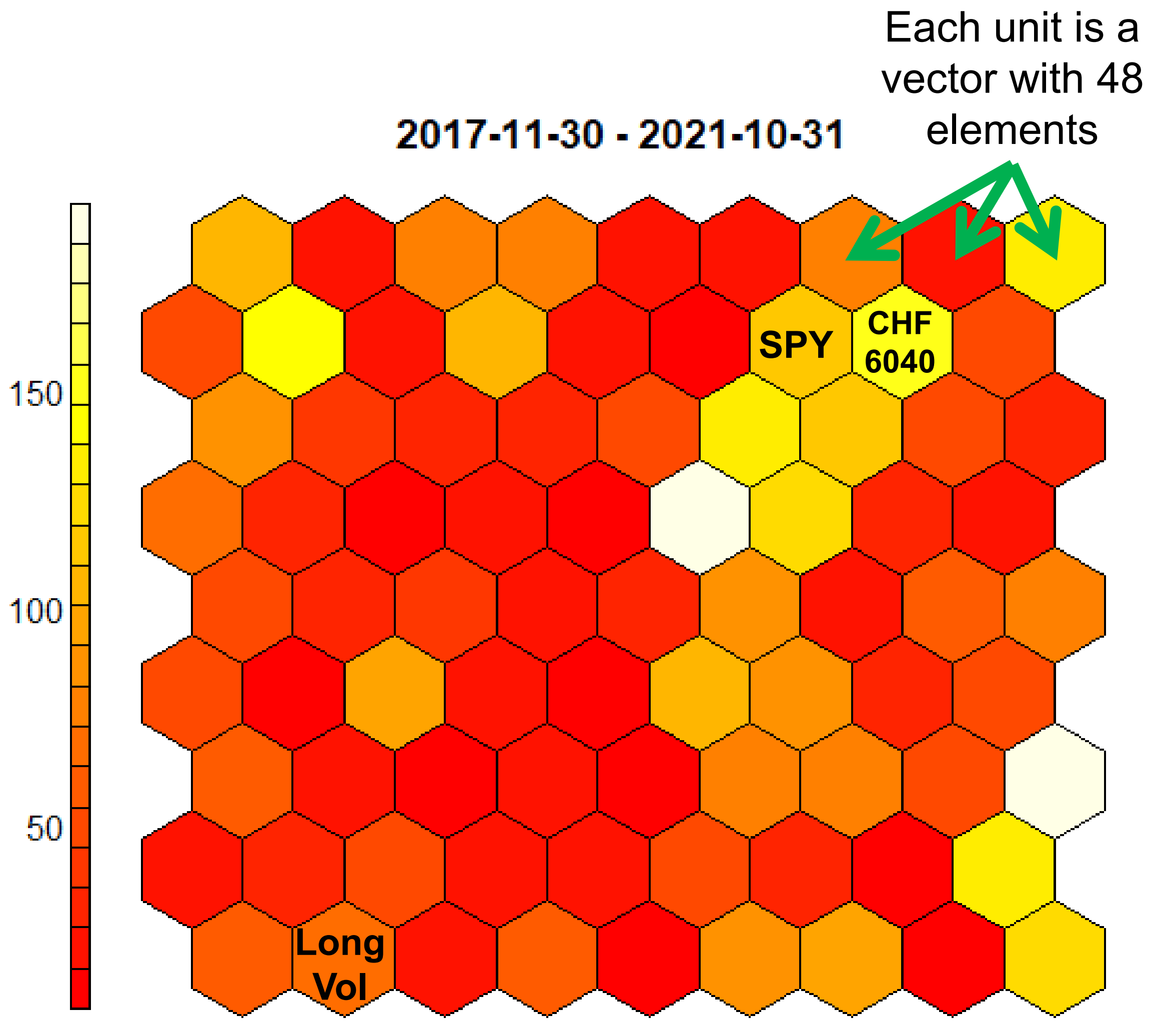
Long Vol Strategy: Returns-based Analysis.

- Analyse potential similarities in the risk profile of a handful of long-vol strategies and a comprehensive ETF universe
- 14,320 ETFs were screened for suitability of study
  - Source of the ETFs: 2022 J.P. Morgan Global ETF Handbook
- 4,622 ETFs passed eligibility criteria (e.g., no stale data, fund history at least 4 Y)
- Data period in-sample 2017-11 to 2021-10 (48 months)
  - This gives an input matrix 48 x 4,622
  - Monthly returns downloaded from Bloomberg
- Monthly returns of those vehicles were fed to the Self-Organising Map (coded in R)
- Out-of-sample 11-2021 to 10-2022 (12 months)

Long Volatility Strategy: Visual Representation.

- Self-Organising Map (SOM, Kohonen (1982, 2001, 2013): project objects on a map
- Similar objects are being projected closely together
- Example: investment vehicles (e.g., managers or ETFs)
- Vehicles with similar return profiles appear on the same unit
- Colour coding: #managers or ETFs mapped onto units

- We want to study impact of Long Vol-strategy on a simple 60% equity / 40% bond portfolio in CHF (**CHF6040**):
    - MSCI World converted to CHF 60% (URTH US Equity)
    - Global Bond ETF (IGLO SW Equity: iShares Global Govt Bond UCITS ETF) in CHF 40%



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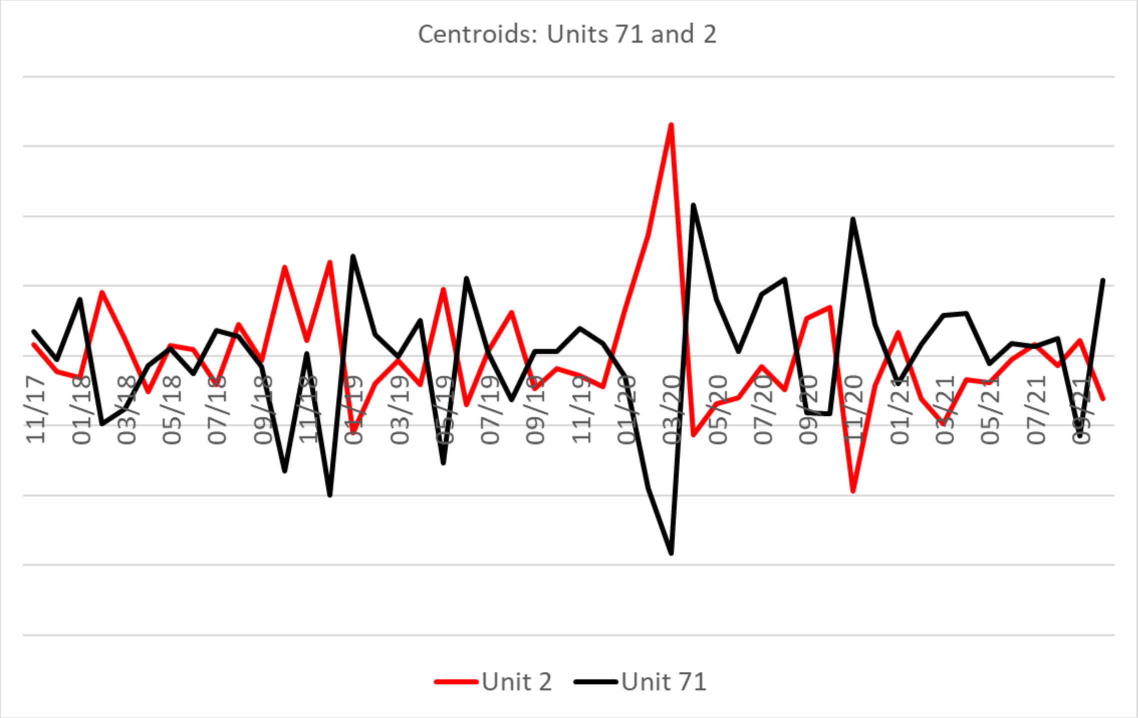
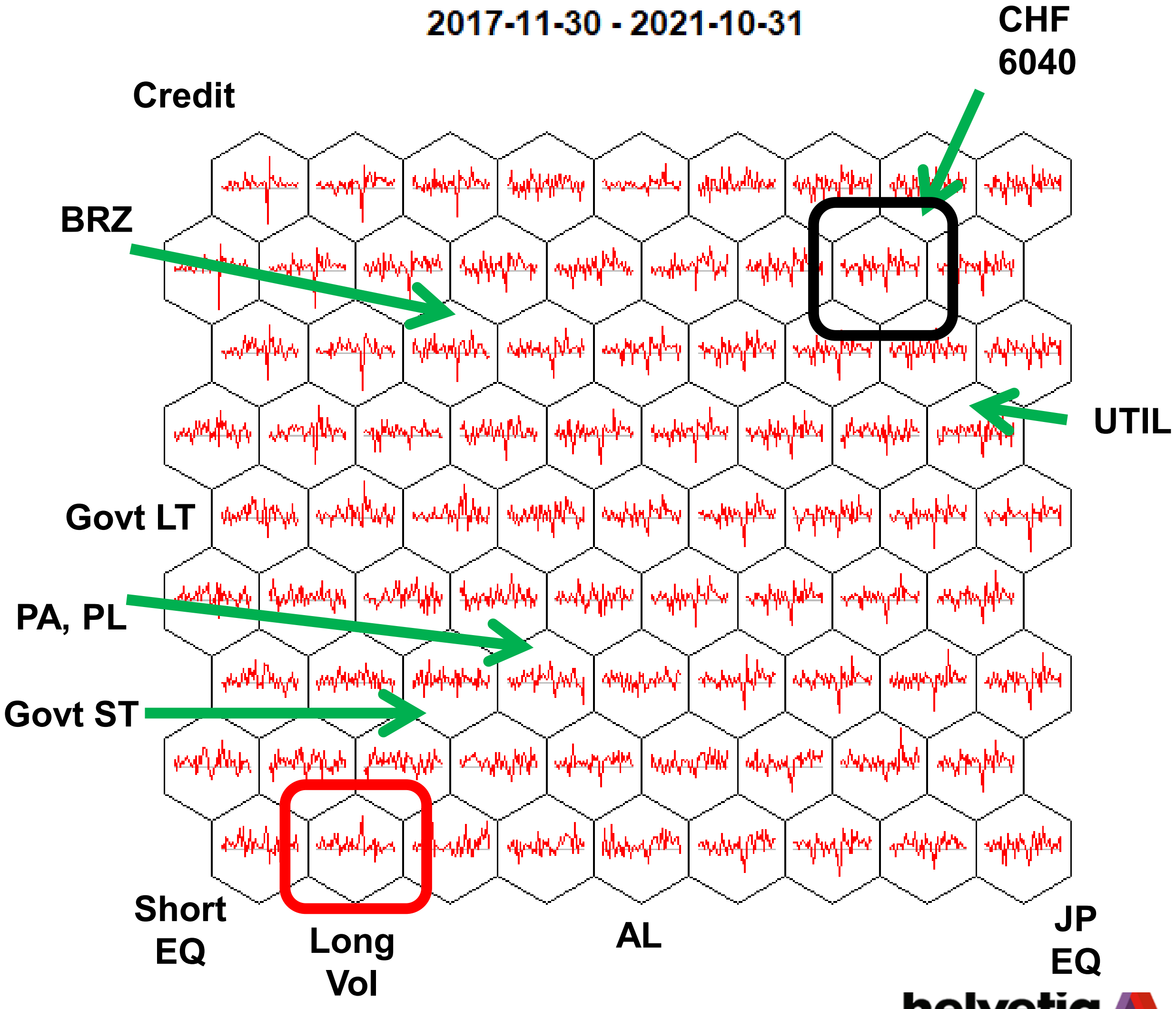
Long Volatility-Strategy: Codebooks.

- Codebook vectors = "Representatives"
- Codebook vectors in the chart on the right
- Codebooks are in-sample only (48 months)

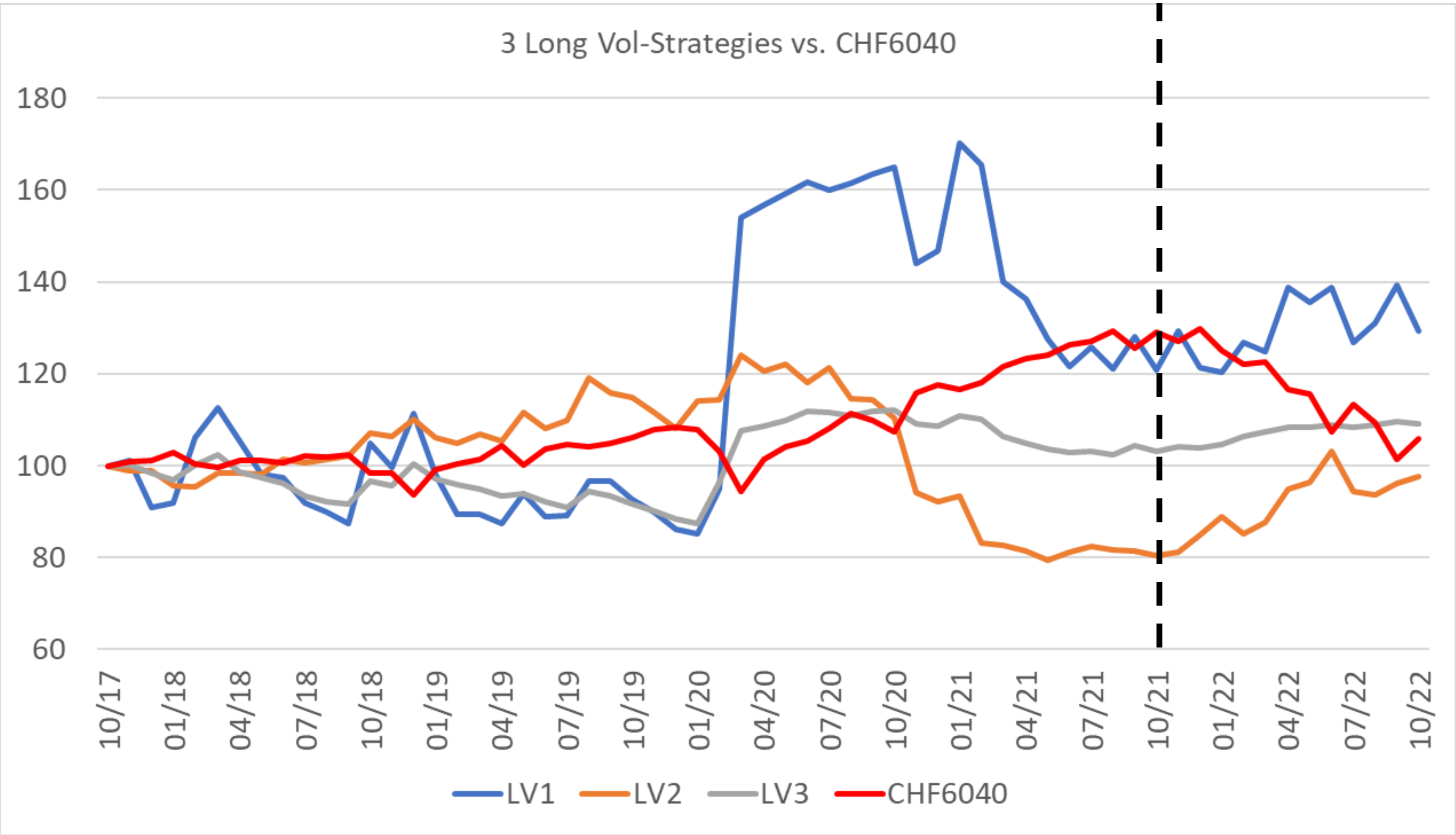




Long Volatility Strategies: Equity Lines.

- Compare 3 Long Vol managers & ETFs from area around unit 2
- LV1 exhibits a strong drawup during Covid in 3/20 and also helps during 2022
- LV2 also benefits from Covid vol, but much less than LV1, and bleeds strongly post-Covid. LV2 also supports in 2022
- LV3 performs more smoothly, but does not really provide tail risk insurance

- Conclusion: LV1 provides most "bang for the buck"



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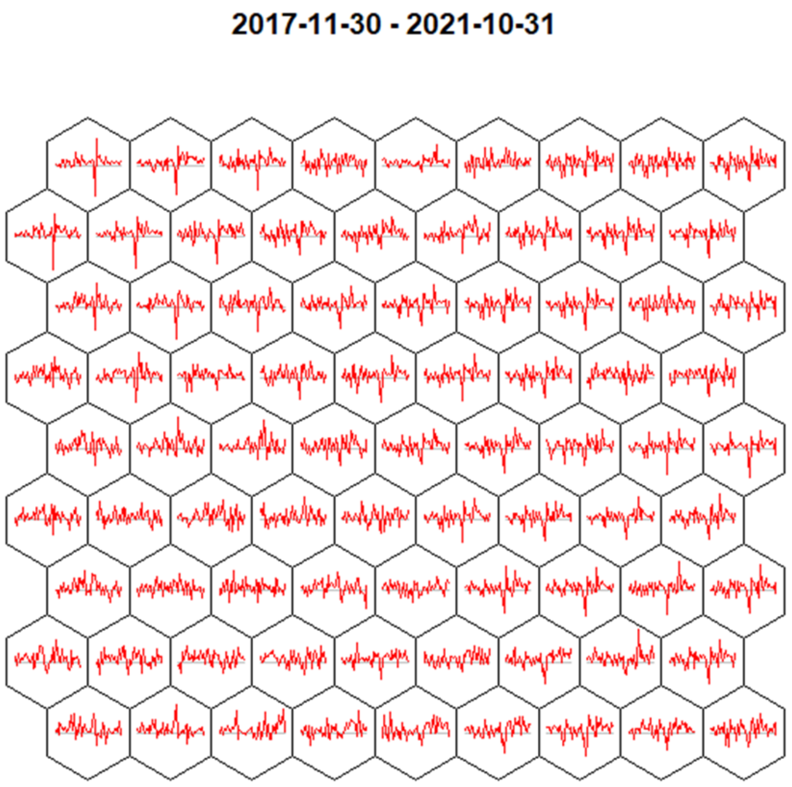
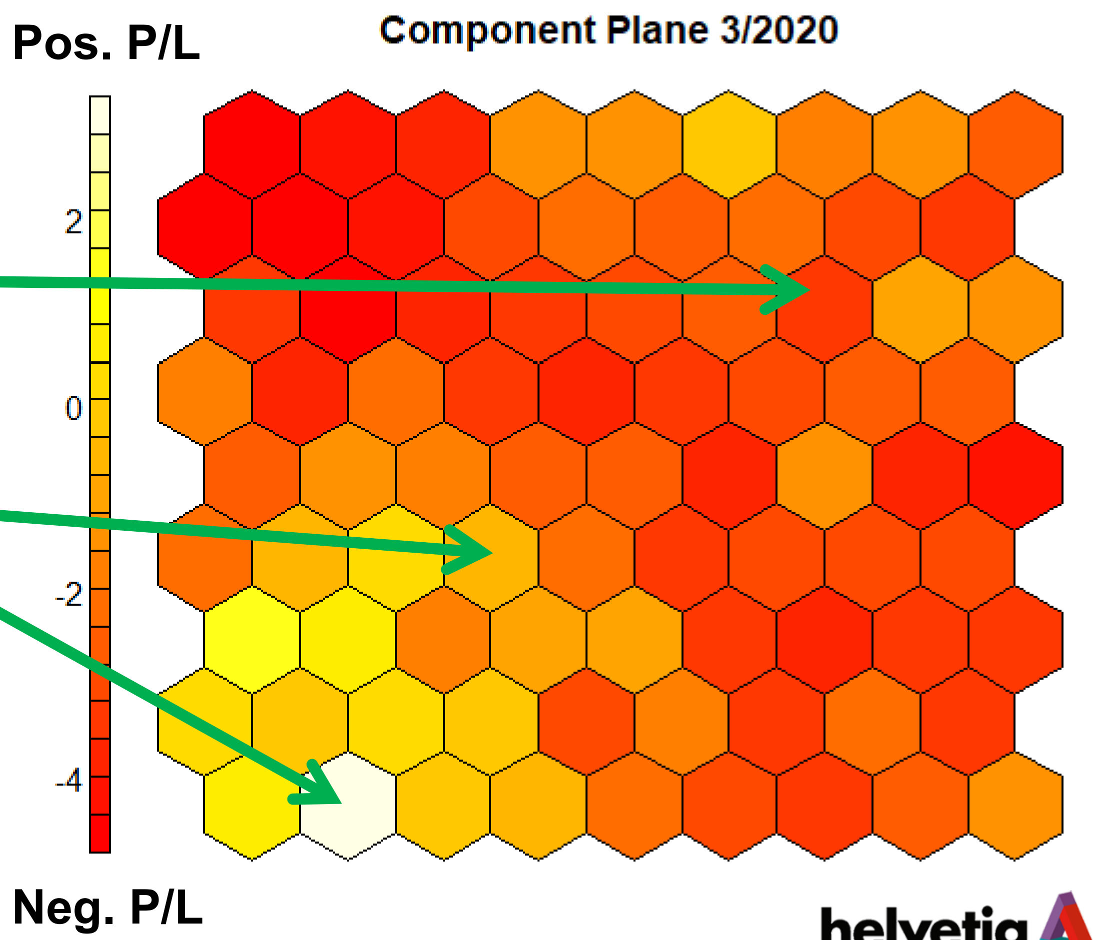
2) Portfolio Construction.

- Can we use the characteristics of the SOM for portfolio construction?
- Codebooks and position on the SOM to identify potentially interesting strategies
- Component Plane for stress analysis (see next slide)



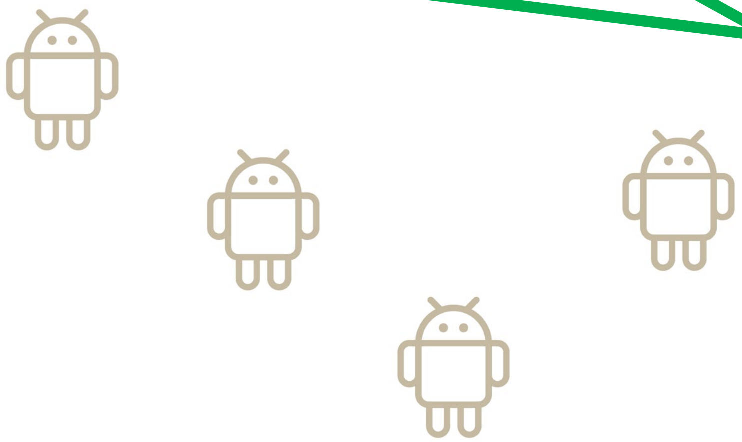
Scenario Analysis: Component Plane. Worst Equity Month 3/20: SPX –8.4%

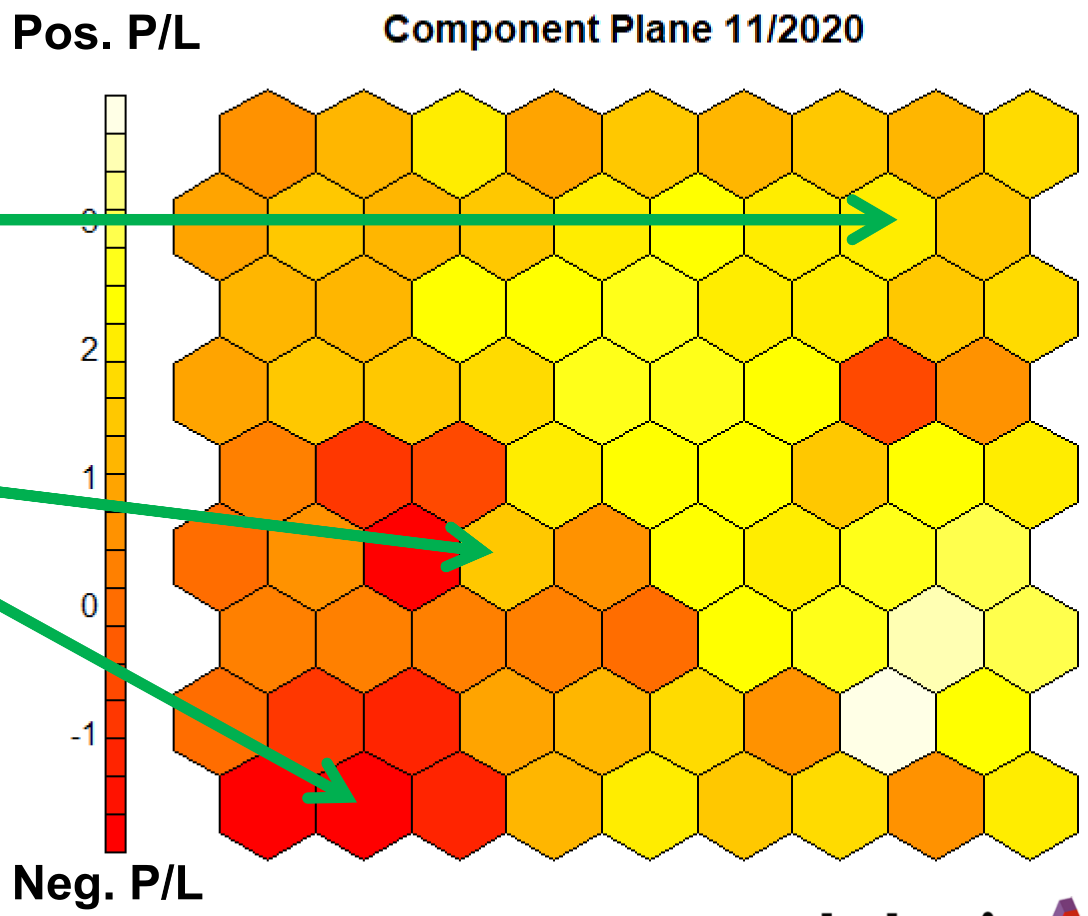
- Component Plane shows how managers fared in the month of worst equity performance: Mar 2020
  - From our matrix 48 x 4622 we pick the row vector with time index "Mar 2020"
- Colour coding shows heavy losses for equities
- Strong gains for Long Vol Strategies
- In-between



Scenario Analysis: Component Plane. Best Equity Month 11/20: SPX +7.9%

- Best equity month: Nov 2020
  - From our matrix 48 x 4622 we pick the row vector with time index "Nov 2020"
- Equities
- Losses for Long Vol Strategies
- In-between





Visual Portfolio Construction.

- Pick managers from different parts of the SOM
  - From each unit pick the manager that most closely resembles the codebook vector, see also appendix
- Table below is a stylised 9 x 9 SOM
  - Numbers in cells are the units' index numbers
  - We start counting from unit 1 in the bottom left corner
  - Unit 81 is in the top right corner
- Units from which we picked managers give the units' style and portfolio weights, e.g., unit 2: Long Vol, 5%

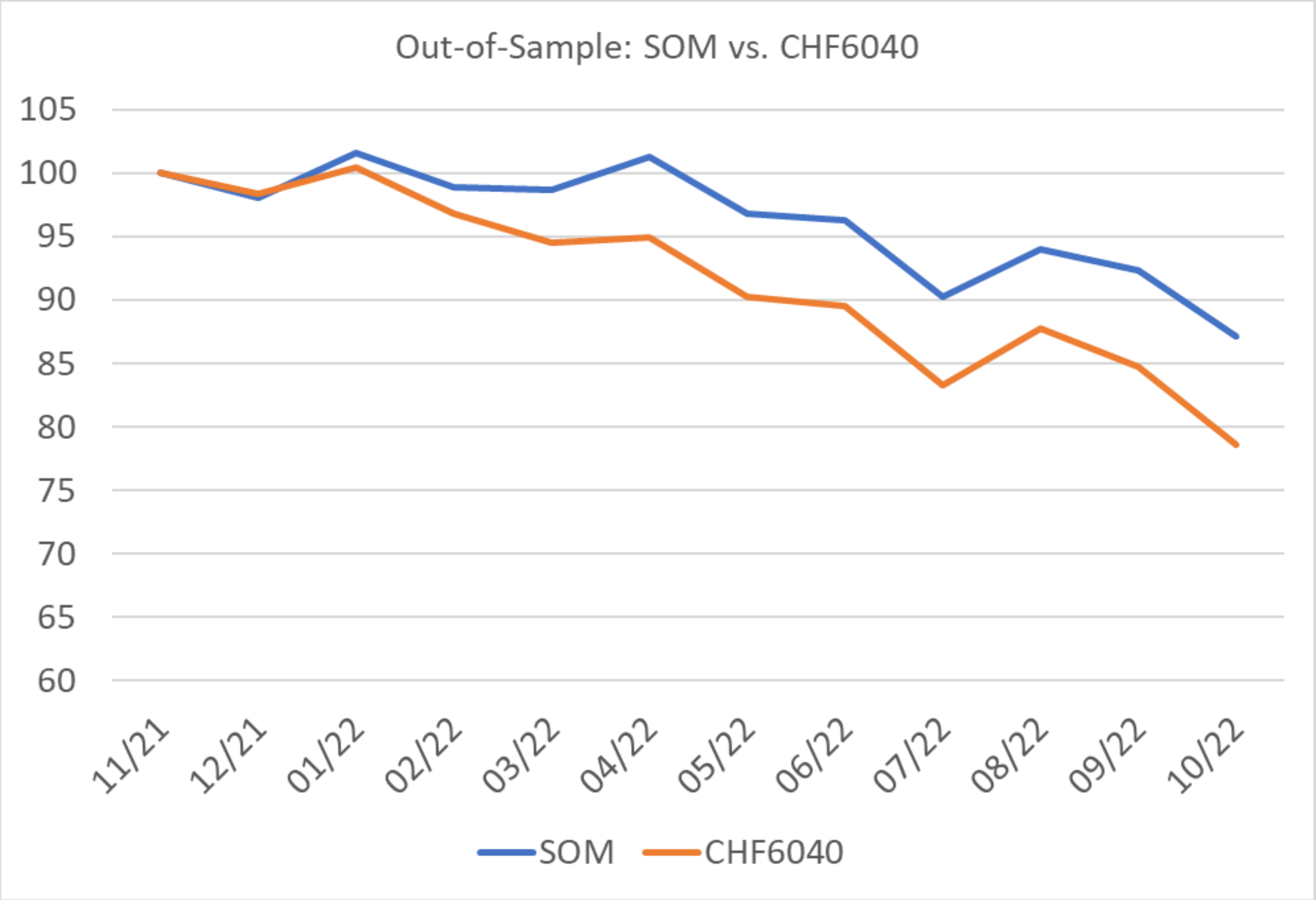
Credit, 25	74	75	76	77	78	79	80	81
64	65	66	67	68	69	70	EQ, 40	72
55	56	EQ BRZ, 5	58	59	60	61	62	EQ SW, 5
46	47	48	49	50	51	52	53	EQ UTIL, 5
37	38	39	40	41	42	43	44	45
28	29	30	31	32	33	34	35	36
19	20	GOVS, 5	22	23	24	25	26	27
10	11	12	13	14	15	16	17	18
1	Long Vol, 5	3	4	AL, 5	6	7	8	EQ JP, 5

Visual Portfolio Construction.

- Our SOM portfolio outperforms CHF6040

	SOM	CHF6040
Return	-10.2%	-18.0%
Vol	12.5%	14.3%

- SOM portfolio still dominated by equity risk, vol reduced



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Summary.

- Visual Risk Analysis can help to better understand structure in data
- SOM is used as quantitative first step of analysis
- SOM maps Long Vol strategies on the opposite side of equity risk
- SOM for risk analysis: if the assets of an existing portfolio come all from the same part of the SOM, there is little diversification to expect in times of crisis
  - Pick assets from all over the SOM
- SOM helped with:
  - Finding strategies that provide "Bang for the buck": upside potential if volatility spikes
  - Find peers of a suggested Long Vol strategy
  - Are there alternatives to the offered strategy that potentially even fit better to our current porfolio?
  - There could be additional interesting alternatives in the surrounding area of unit 2
- Characteristics of the SOM can be used for Portfolio Construction
- Fresh perspective to "classic" research
- Visual representation useful in client conversations
- ML tools are definitely useful and add insights, but **NOT** a money machine

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References.

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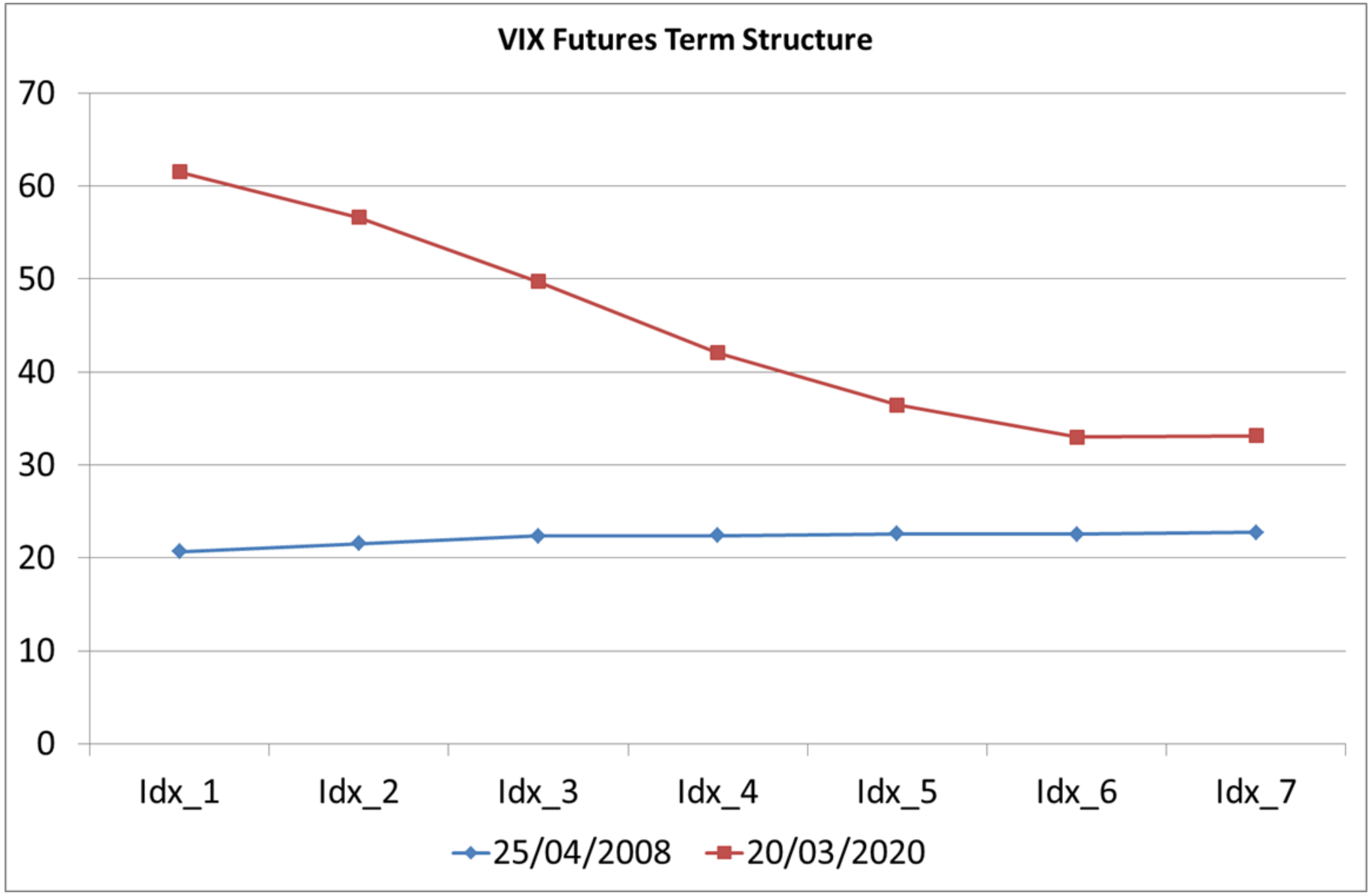
Appendix.

VIX Futures.

- VIX futures: first 7 expiries



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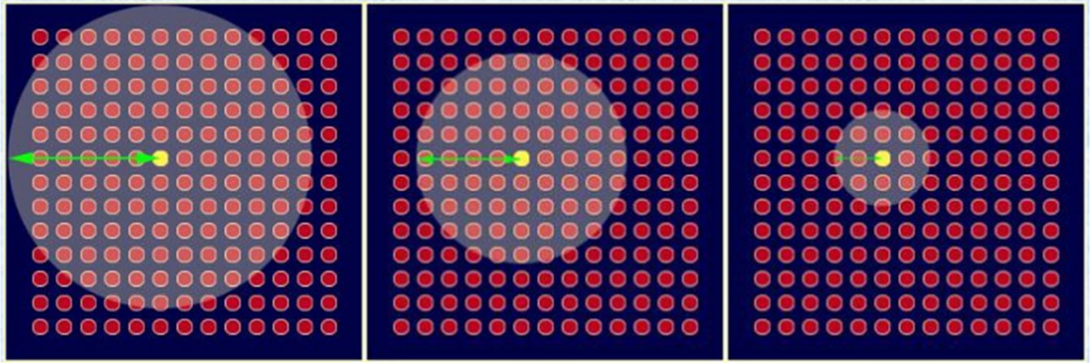
How Do SOM “Learn”?

- Learning = creating “good” representatives, i.e., the units of the SOM are calibrated such that they represent a subset of the sample
  - For our SOM with 81 units, we have 81 vectors with 48 elements each → codebook vectors



1. The units are often initialised with random numbers, also PCA or other methods
2. Samples are presented to the SOM
3. Identify the unit most similar to the current sample or sample subset (Best Matching Unit or BMU)
4. Update units to become more similar to the sample
   - Early in the learning phase, many units are updated
   - Late in the learning phase, only a few (or only one unit) is updated
5. Loop back to step 2 until map error does not change anymore

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How Do SOM “Learn”?

- The learning rate α determines the size of the weight adjustment, the neighbourhood function $\theta(t)$ the radius around the BMU:

$$w_{ij}(t+1) = w_{ij}(t) + \theta(t) \cdot \alpha(t) \cdot \left(x_i(t) - w_{ij}(t)\right)$$

  - $x_i(t)$: characteristics of the samples, e.g., returns of manager i at learning cycle t
- For example, α = 0.05 means that centroids’ weights get adjusted by 5% of the difference between sample and existing weight
- $\theta(t)$ starts with a large value to include many units in the weight adjustment process and ends with only 1 unit (= BMU) being adjusted
- If only the BMU would be updated, the SOM would yield identical results as k-Means

- How many and which neighbouring units are updated depends on the neighbourhood function $\theta(t) \rightarrow$ this is one of the reasons how non-linearity can be reflected in the SOM

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Distance Measure, Portfolio Construction.

- Managers are projected onto the units of the SOM based on their proximity to the BMU
- Distance measure is the Euclidean Distance:
  - $x_{i,t}$: returns of unit i at time t
  - $x_{j,t}$: returns of manager j at time t

$$\text{ED}= \sqrt{\sum_{t=1}^{T}\left(x_{i,t} - x_{j,t}\right)^2}$$

- How can we select managers for Portfolio Construction?
- Two managers are mapped onto the same unit
  - We have 3 vectors with monthly returns: 2 managers and 1 codebook
  - One of the two managers resembles the codebook more closely than the other, e.g., ED(Manager 1) < ED(Manager 2) → Unit resembles M1 more closely than M2

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